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Interpretable Machine Learning for Multi-Crop Yield Prediction in Semi-Arid Regions: A Hierarchical Approach to Handle Climate Data Sparsity

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This study develops a hierarchical machine learning framework to address the challenges of multi-crop yield prediction in semi-arid regions, focusing on sparse climate data, model interpretability, and heterogeneous climate-crop interactions. The framework integrates Random Forest (RF) techniques for crop-specific modeling, exploiting their robustness to nonlinear relationships in small datasets, while long short term memory (LSTM) networks extract long-term climate trends, and Convolutional Neural Network (TCNN) with dilated kernels capture multi-scale temporal dependencies, creating a complementary hierarchy that leverages the strengths of each approach. Missing weather data (gaps of 8.3–45.2%) are addressed via Multiple Imputation by Chained Equations (MICE), incorporating climatological constraints to preserve physical consistency. Model interpretability is achieved through SHapley Additive exPlanations (SHAP) analysis and uncertainty decomposition, quantifying the contributions of data variability, temporal dynamics, and model ensembles. Validated on 13 years of agricultural data (2010-2022) from the semi-arid Ouarzazate region of Morocco, the framework achieved R^2 values of 0.77 (cereals), 0.73 (vegetables), and 0.70 (tree crops), representing a 12-18% improvement over conventional single-model approaches which typically achieve R^2 values of 0.65-0.68 in similar semi-arid conditions with complete datasets. SHAP analysis identified crop-specific critical thresholds, including maximum summer temperatures (>40°C) for vegetables and winter precipitation (<30mm) for cereals, while uncertainty quantification revealed that transition seasons (spring/autumn) are high-risk periods with prediction variances exceeding ±1.5 T/ha. Performance declines during extreme weather events (e.g., unprecedented droughts) that are absent from historical data, and soil moisture dynamics remain excluded. Future work will address these limitations through integration of soil moisture sensors, development of transfer learning approaches for extreme weather events. Practical applications include optimizing irrigation schedules using SHAP-derived temperature thresholds and prioritizing resource allocation during periods of high uncertainty. This work represents a novel unified framework combining imputation, temporal modeling, and crop-specific interpretability for semi-arid systems, going beyond black-box models or single-crop approaches.

Keywords: Hierarchical machine learning, agricultural yield prediction, multi-crop systems, shap interpretability, missing meteorological data.

INTRODUCTION

Crop yield prediction in semi-arid regions faces major challenges due to climate variability, complex crop interactions, and scarce climate data. These regions, characterized by limited water resources and increasingly unpredictable climate conditions, require accurate crop yield predictions for food security and economic planning as discussed by El Kenawy (2024).

Existing machine learning approaches for crop yield prediction in semi-arid regions typically overlook multi-cropping dynamics, require extensive climate datasets unavailable in data-sparse environments, and lack interpretability for stakeholders. These black-box models fail to capture the complex interactions between different crops competing for limited resources, significantly limiting their practical utility in semi-arid agricultural systems where climate variability and crop interdependencies critically influence production outcomes.

Traditional approaches to crop yield prediction have typically focused on individual cropping systems or relied on comprehensive climate datasets, making them unsuitable for

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semi-arid regions where climate data are often scarce and multiple crops compete for limited resources (Singh *et al.*, 2024). Although machine learning methods have shown promising potential in agricultural applications, they often lack interpretability and struggle to handle the complex patterns of missing data characteristic of semi-arid regions (Drogkoula *et al.*, 2023). This gap is particularly pronounced in heterogeneous farming systems, where different crops exhibit varying sensitivities to climate conditions (Altieri and Nicholls, 2017).

The objective of this study is to develop a hierarchical machine learning framework to improve yield predictions in multi-cropping systems in semi-arid regions by simultaneously addressing climate data gaps and providing interpretable results. The framework provides immediate practical value for agricultural stakeholders: policymakers gain evidence-based tools for resource allocation and food security planning, while farmers benefit from interpretable thresholds for irrigation scheduling and crop selection. By quantifying prediction uncertainty across seasons, the approach helps identify high-risk periods requiring intervention, translating complex climate-crop relationships into management strategies.

The research is based on the hypothesis that integrating crop-specific responses with common climate trends within a hierarchical structure will result in higher prediction accuracy compared to traditional single-level approaches. Furthermore, integrating an interpretability layer is expected to generate actionable insights for agricultural stakeholders on the key drivers of crop yield variability. This research aims to fill a critical gap in current methodologies, as existing interpretable machine learning approaches in agriculture have largely neglected the specificities of multi-cropping systems as well as the practical implications of data sparsity (Nayak *et al.*, 2022; Gautam *et al.*, 2024). The proposed framework makes three main contributions:

First, a robust methodology for dealing with sparse climate data in semi-arid regions, combining climate trend recognition and uncertainty estimation.

Second, a new model architecture that explicitly considers both crop-specific responses and common climate forcings. This architecture captures the unique characteristics of cereals, vegetables, and tree crops while incorporating common trends in their responses to climate variation.

Finally, an interpretable approach that provides insights into the relationships between climate variables and crop yield, facilitating decision-making for farmers and policy makers.

The remainder of this paper provides a review of relevant work on crop yield prediction and explainable machine learning, followed by a description of the study area and dataset characteristics. The methodology section details the development of the hierarchical framework structure and the interpretability approach. The results demonstrate the effectiveness of the proposed framework through a comparative analysis with existing methods. The discussion explores the practical implications as well as the limitations of the approach. Finally, the paper concludes with recommendations for future research directions.

Recent developments in agricultural crop yield prediction have seen a shift from traditional statistical methods to ML approaches (Ed-Daoudi *et al.*, 2023). This section reviews the relevant literature in three main areas: agricultural crop yield prediction methods, interpretable machine learning techniques, and approaches to handling missing data in agricultural models.

***Agricultural yield prediction*:** Traditional techniques for crop yield prediction have relied heavily on statistical methods such as regression analysis and time series forecasting. Linear regression models have been widely used for their simplicity and interpretability, but they often fail to capture the complex nonlinear relationships between environmental factors and crop yields (Park *et al.*, 2005). Time series methods, including autoregressive integrated moving average (ARIMA) and its variants, have shown success in capturing temporal patterns but struggle with incorporating multiple environmental variables (Praveen and Sharma, 2020).

ML has emerged as a promising approach to crop yield prediction, with methods ranging from support vector machines (SVMs) to artificial neural networks (ANNs) (Jabed and Murad, 2024). Deep learning models have shown particular success in capturing complex patterns in agricultural data. However, these approaches typically require large, complete datasets and often operate as black boxes, making their implementation difficult in regions with sparse data collection (Attri *et al.*, 2023).

In semi-arid regions, crop yield prediction faces unique challenges due to high climate variability and complex soil-water interactions (Naorem *et al.*, 2023). Research has shown that current machine learning approaches often underperform under these conditions, especially when dealing with multiple crop types simultaneously (Mandal and Chanda, 2023). The specific challenges of multi-cropping systems in semi-arid regions remain inadequately addressed in current forecasting frameworks.

***Interpretable machine learning*:** The field of interpretable machine learning has evolved significantly, with approaches ranging from simple feature importance measures to sophisticated model-independent interpretability techniques (Marcinkevičs and Vogt, 2023). SHAP values have emerged as a well-established theoretical approach to model interpretability, providing local and global explanations of model predictions (Tursunalieva *et al.*, 2024). However, their application in agricultural contexts has been limited, particularly in multi-cropping systems.

Recent advancements in machine learning have led to the development of explainable and interpretable models, which show great potential in handling complex, interconnected outputs (Khaldi *et al.*, 2025). These approaches show promise

in handling multiple interconnected outputs but have not been widely applied to agricultural crop prediction. The challenge of maintaining interpretability while handling missing data remains particularly relevant in agricultural applications (Cravero *et al.*, 2022).

***Missing data handling in agricultural models*:** Handling missing data in agricultural models has traditionally relied on simple imputation methods or complete case analysis (Zhang and Thorburn, 2022). More sophisticated approaches, including multiple imputation and expectation maximization algorithms, have been proposed, but they do not take into account the specific characteristics of agricultural time series data (Thulare *et al.*, 2021).

Recent research has explored the use of deep learning methods to handle missing data in environmental time series (Tzoumpas *et al.*, 2024). These approaches show promise in capturing complex temporal dependencies but often lack interpretability and struggle with the sparse nature of data in semi-arid regions (Baig *et al.*, 2024). The interactions between handling missing data and model interpretability remain an active area of research, particularly in the context of agricultural applications.

This literature analysis reveals several key gaps:

- Limited research on interpretable machine learning approaches specifically designed for multiple cropping systems
- Insufficient attention to the challenges of missing climate data in semi-arid regions;
- Lack of frameworks that simultaneously address forecast accuracy, interpretability, and handling missing data
- The need for methods that can provide field-relevant understanding of the agricultural sector while maintaining scientific rigor

The present work addresses these gaps by proposing a hierarchical Machine Learning framework that integrates missing data processing with interpretable predictions for multi-cropping systems in semi-arid regions, in order to improve agricultural yield predictions while providing farmers and agricultural managers with clear, practical information for optimal resource allocation and crop management decisions.

MATERIALS AND METHODS

Understanding crop production dynamics in semi-arid regions requires a comprehensive analysis of both agricultural and meteorological data. This section reviews the dataset used in the research, which includes crop production records and meteorological measurements from 2010 to 2022. These datasets combine multiple crop types with climate variables over different time periods, creating unique challenges in data integration and quality assessment.

***Study region characteristics*:** The study area is located within the perimeter of the Regional Office for Agricultural Development of Ouarzazate (ORMVA), in the center of southern Morocco, on the edge of the Sahara Desert. It is located at an altitude of approximately 1,160 meters above sea level and is characterized by a semi-arid climate with strong temperature variations both daily and seasonal (ORMVAO, 2025).

The climate is marked by hot summers, where temperatures often exceed 40 °C, and mild winters, with temperatures sometimes falling below zero. Annual precipitation is low, with an average of 120 mm, and shows strong interannual variability. The region experiences high evaporation rates, reaching an average of 2,194.7 mm per year, which has a significant impact on agricultural water resource management (Houssni *et al.*, 2023). Agricultural practices in the area are adapted to these harsh climatic conditions. The farming system is predominantly small-scale, with a mix of traditional and modern irrigation techniques. The main cropping pattern includes:

- Cereals (primarily wheat and barley) cultivated during the winter season
- Vegetables (including tomatoes, onions, and carrots) grown year-round in irrigated areas
- Tree crops (dominated by date palms and olive trees) as permanent cultures

The socio-economic context is characterized by a high dependence on agriculture for local livelihoods. About 60% of the local population depends directly or indirectly on agricultural activities. The region has benefited from significant investments in irrigation infrastructure in recent decades, although water scarcity remains a major constraint for agricultural development. In recent years, there has been a gradual shift towards more drought-resistant crops and the adoption of more efficient irrigation technologies, reflecting adaptation to increasingly variable climatic conditions (Adraoui and Jaafar, 2024).

***Dataset description*:** Official agricultural and meteorological records were obtained from ORMVA Ouarzazate's administrative database, covering the period 2010-2022. This official dataset includes detailed temporal monitoring of agricultural production and environmental parameters. This provides a good understanding of agricultural activities in the region.

***Agricultural data*:** The agricultural dataset encompasses three primary crop categories monitored during the study period:

- Cereals (wheat, barley): yields averaging 32.7 T/ha (std: 6.8 T/ha, range: 22.4-47.0 T/ha)
- Vegetables (onions, carrots, tomatoes): yields averaging 31.8 T/ha (std: 9.2 T/ha, range: 11.1-51.5 T/ha)
- Tree Crops (date palms, olive trees): yields averaging 42.3 T/ha (std: 12.1 T/ha, range: 18.0-70.0 T/ha)

Production data is recorded in quintals (q) for cereals and metric tons (T) for other crops, with yields documented on a per hectare basis. Crop production records show complete data coverage with no missing values during the study period, showing distinct seasonal cycles with peak production periods for every crop type.

Meteorological data: The meteorological data has monthly temporal resolution collected from 3 weather stations within the study area (average station distance: 45km). Variables include daily maximum, minimum, and average temperatures (°C), precipitation (mm), evaporation (mm), wind speed (km/h), and solar insolation (hours). Table 1 presents the descriptive statistics of key meteorological parameters, highlighting the significant variability in climatic conditions during the study period.

Table 1. Descriptive statistics of key meteorological variables (2010-2022).

Variable	Mean	Std Dev	Min	Max	Missing Data (%)
Temperature (°C)					
Maximum	32.5	5.2	22.0	45.0	15.2
Minimum	15.8	4.9	2.0	28.0	15.2
Average	24.2	4.8	12.0	36.5	15.2
Other Meteorological Parameters					
Precipitation (mm)	11.2	15.3	0.0	85.4	8.3
Evaporation (mm)	182.9	45.8	95.5	298.4	42.1
Wind Speed (km/h)	12.5	3.8	5.2	25.4	38.7
Insolation (hours)	241.7	38.5	180.0	315.0	45.2

Temperature measurements show consistent patterns of missing data (15.2%):

- Maximum temperatures: 32.5°C ± 5.2°C (range: 22.0-45.0°C)
- Minimum temperatures: 15.8°C ± 4.9°C (range: 2.0-28.0°C)
- Average temperatures: 24.2°C ± 4.8°C (range: 12.0-36.5°C)

Temperature variables demonstrate strong seasonal patterns with maximum amplitudes during summer months (June-August) and minimum variations during winter periods (December-February).

Additional meteorological parameters exhibit varying degrees of data completeness:

- Precipitation: 11.2 ± 15.3 mm (range: 0-85.0 mm, 8.3% missing)
- Evaporation: 182.9 ± 45.8 mm (range: 95.5-298.4 mm, 42.1% missing)
- Wind Speed: 12.5 ± 3.8 km/h (range: 5.2-25.4 km/h, 38.7% missing)
- Solar Insolation: 241.7 ± 38.5 hours (range: 180.0-315.0 hours, 45.2% missing)

Precipitation patterns show high interannual variability, with concentrated rainfall events (>30mm) during winter months, and long dry periods (<5mm) frequently observed during summer.

The temporal resolution varies by parameter type:

- Crop production data: Annual records
- Meteorological data: Monthly measurements
- Management practices: Seasonal documentation

This dataset represents one of the most comprehensive agricultural monitoring operations in the region. However, many temporal gaps exist, particularly in meteorological parameters during the later years of the study period (2018-2022).

***Cross-correlations between variables*:** Analysis of variable relationships reveals significant interactions between meteorological parameters and crop yields in the studied regions. The correlation patterns are visualized in figure 1.

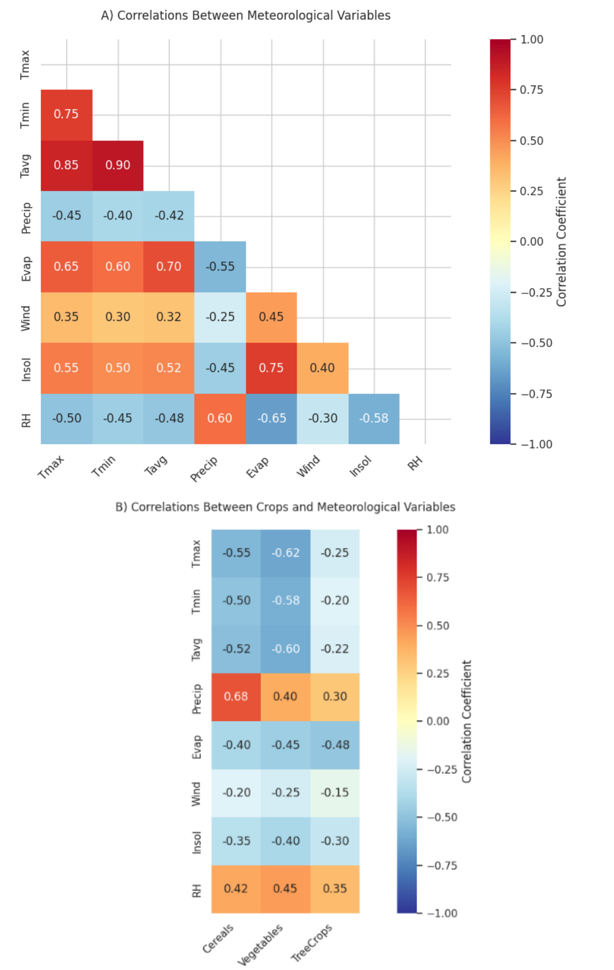

Figure 1. Correlation analysis of agricultural and meteorological variables.

This reveals clusters of related variables, particularly among temperature measurements and their relationships with agricultural outputs.

- Strong positive correlations (r > 0.7) between:
  - ✓ Monthly evaporation and solar insolation duration
  - ✓ Average temperature and evaporation rates
- Moderate negative correlations (-0.6 < r < -0.3) between:
  - ✓ Monthly precipitation and temperature variables
  - ✓ Monthly precipitation and evaporation rates
  - ✓ Relative humidity and solar insolation duration
- Crop-specific correlations:
  - ✓ Cereal yields show strong positive correlation with winter precipitation (r = 0.68) and negative correlation with maximum winter temperatures (r = -0.55)
  - ✓ Tree crop yields demonstrate resilience to temperature variations (r = -0.25) but moderate sensitivity to cumulative summer evaporation (r = -0.48)
  - ✓ Vegetable yields exhibit strong negative correlation with maximum summer temperatures (r = -0.62) and positive correlation with relative humidity (r = 0.45)

The correlation patterns show the interactions between climatic variables and their differential impacts on crop productivity in this semi-arid environment. These relationships prove the important role of water-related variables (precipitation, evaporation, and humidity) in determining agricultural results.

This section describes the proposed hierarchical framework that addresses both the complexity of crop-climate interactions and the challenge of missing meteorological data.

Overall framework: The proposed methodology presents a hierarchical structure that separates the modeling process into different but connected layers, each addressing specific aspects of the yield prediction.

The framework presented in figure 2 consists of three main layers.

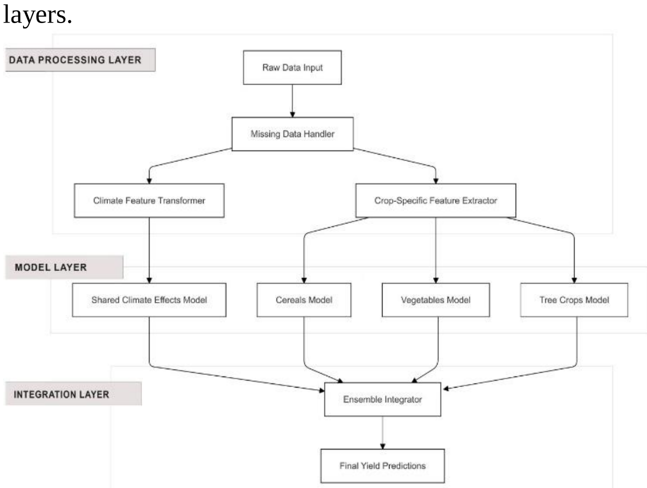

Figure 2. Hierarchical model architecture.

The Data processing layer serves as the foundation of the architecture, handling the initial steps of data preparation and transformation. This layer preprocesses raw input data by first applying standardization to meteorological variables and crop yields (Sudhamathi and Perumal, 2024), following:

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

Where X represents the raw values, μ is the mean, and σ is the standard deviation. The layer then addresses the challenges of missing data through the multiple imputation by chained equations (MICE) approach (Saini and Nagpal, 2024), which can be represented as follows:

$$X_{miss} = E(X_{miss} | X_{obs}, R, \theta) \quad (2)$$

Where X_{miss} represents the imputed values, X_{obs} represents the observed data, R is the missingness pattern, and θ represents the parameters of the imputation model. This approach is important given the varying rates of missing data across meteorological variables (8.3-45.2%). The imputation process includes temporal patterns and physical constraints, ensuring that imputed values maintain climatologically coherent relationships.

The MICE implementation used 50 iterations with 10 imputations per missing value. Physical constraints were enforced including: temperature relationships (T_max > T_avg > T_min), precipitation non-negativity, and climatologically plausible ranges for each variable based on historical records. Chain equations incorporated seasonal patterns with trigonometric terms capturing monthly cycles.

The layer then performs targeted feature engineering by transforming raw meteorological measurements into agriculturally relevant indicators through several key computations:

- Growing Degree Days (GDD), which is a critical thermal time indicator (Gürkan *et al.*, 2022), is calculated using crop-specific base temperatures (typically 10°C for cereals for example):

$$GDD = \sum \max\left(0, \left(\frac{T_{max} + T_{min}}{2} - T_{base}\right)\right) \quad (3)$$

- Vapor Pressure Deficit (VPD), which influences crop water demand (Dong *et al.*, 2024), is derived from air temperature and relative humidity:

$$VPD = e_s(T_{air}) \times \left(1 - \frac{RH}{100}\right) \quad (4)$$

- Reference Evapotranspiration (ET_0) is computed using the FAO Penman-Monteith equation (Ippolito *et al.*, 2024):

$$ET_0 = \frac{0.408\Delta(Rn - G) + \gamma(\frac{900}{T + 273})u2(es - ea)}{\Delta + \gamma(1 + 0.34u_2)} \quad (5)$$

Where parameters include mean temperature, wind speed, and vapor pressure components.

These agroclimatic indices are then aggregated to better represent the environmental conditions affecting yield formation.

The model layer presented in figure 3 builds upon the processed data through a parallel structure that captures different aspects of yield prediction.

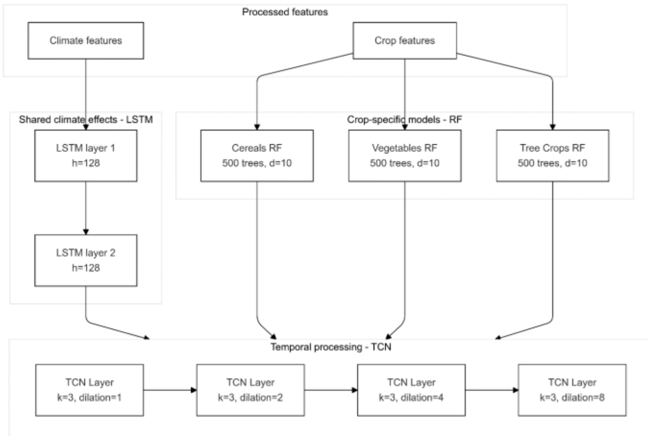

Figure 3. Overview of the model layer.

This layer includes an LSTM network as the shared climate effects model that identifies common environmental influences across all crop types, while simultaneously maintaining crop-specific RF models adapted to the unique characteristics of cereals, vegetables, and tree crops.

The LSTM architecture, with hidden size h=128 and two layers, is particularly suited for capturing long-term climate dependencies, while RFs, with 500 trees and maximum depth of 10, excel at modeling non-linear crop-specific responses. This hybrid approach is strengthened by a Temporal Convolutional Network (TCN) that processes temporal dependencies in the data, explaining the interactions between environmental factors and crop development over time. The TCN uses dilated causal convolutions with kernel size k=3 and 4 levels of dilation, in order to capture long-range dependencies while maintaining computational efficiency.

RF was selected over other ensemble methods due to its proven robustness when dealing with small, heterogeneous datasets and nonlinear variable interactions common in agricultural systems. LSTM networks were preferred over simpler recurrent architectures for their ability to retain long-term dependencies in climate data while avoiding gradient vanishing problems. TCN with dilated convolutions was chosen for its parallelization efficiency and ability to model variable-length temporal dependencies without the recurrence constraints of RNNs.

The Integration layer represents the final stage of the framework, where outputs from individual models are systematically combined through an ensemble approach. The TCN outputs first process the temporal dependencies, producing a sequence of features that are then combined with the individual model predictions. The final weighted combination follows:

$$\hat{Y} = \alpha \times Y_{TCN} + \sum (w_i \times y_i) \quad (6)$$

Where Y_{TCN} represents the TCN output, α is a learned parameter balancing the temporal and individual model contributions, and the model weights w_i are determined by:

$$w_i = \frac{\exp(-\lambda E_i)}{\sum_j \exp(-\lambda E_j)} \quad (7)$$

Where $exp(-\lambda E_i)$ emphasizes smaller E_i by scaling and negating them, the denominator $\sum_j \exp(-\lambda E_j)$ normalizes the weights to sum to 1, with λ controlling the sharpness of the distribution.

The uncertainty estimation takes into account both the TCN and individual model uncertainties:

$$\sigma_{\hat{y}}^2 = \alpha^2 \sigma_{TCN}^2 + \sum_i w_i^2 \sigma_i^2 + \sum_j w_i w_j (y_i - \hat{y})(y_j - \hat{y}) \quad (8)$$

Where $\alpha^2 \sigma_{TCN}^2$ captures the uncertainty associated with the TCN, scaled by its relative importance α, a larger α assigns more weight to the TCN's variance in the total uncertainty. The term $\sum w_i^2 \sigma_i^2$ represents the individual uncertainties σ_i^2 of additional predictors, weighted by their squared contributions. In addition, $\sum w_i w_j (y_i - \hat{y})(y_j - \hat{y})$ represents the covariance between predictors y_i and y_j , showing how their interactions influence the total uncertainty.

Information flows through the hierarchy as follows:

(1) Preprocessed data feeds both crop-specific RF models and the shared LSTM component simultaneously

(2) RF models extract crop-specific features while LSTM captures temporal climate patterns common across crops

(3) Both outputs feed into the TCN, which models complex temporal dependencies

(4) The integration layer combines these predictions with learned weights that dynamically adjust based on model performance and uncertainty estimation.

Interpretability framework**:** In addition to the presented model's architecture, interpretability must be taken into account as it helps understand and validate the model's predictions. The framework in figure 4 presents an interpretability approach that operates across all the layers to clarify the model decisions and ensure transparency in the predictions.

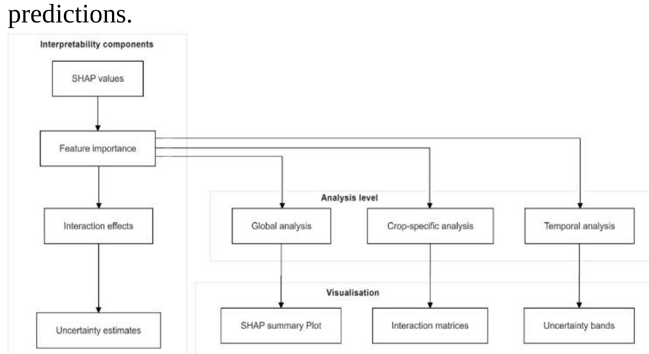

Figure 4. Overview of the interpretability framework.

The interpretability framework begins with the computation of SHAP values to quantify how each feature contributes to individual predictions. The SHAP value for a feature x_i is calculated as:

$$SHAP(x_i) = \sum_{S\subseteq\{1,2,\ldots,n\}\{i\}} \frac{|S|!(n-|S|-1)!}{n!}[fx(S\cup\{i\}) - fx(S)] \quad (9)$$

Where S represents feature subsets, $fx(S)$ is the model prediction with feature subset S, and n is the total number of features. This approach provides a mathematically rigorous foundation for understanding feature contributions based on cooperative game theory principles.

Feature importance analysis is conducted through an approach that aligns with the model's architecture. Global importance metrics are computed by aggregating absolute SHAP values across predictions:

$$GlobalImportance(i) = \sum \frac{|SHAP(x_i)|}{n} \quad (10)$$

This is complemented by crop-specific importance rankings derived from the RF models and temporal importance patterns extracted from the TCN layers, providing a view of feature relevance across different aspects of the prediction task.

The framework extends beyond individual feature contributions to capture interaction effects between features. SHAP interaction values for feature pairs are computed as:

$$\varphi_{ij} = \sum[fx(S\cup\{i,j\}) - fx(S\cup\{i\}) - fx(S\cup\{j\}) + fx(S)] \quad (11)$$

This quantifies how features work together to influence predictions, while temporal interactions are examined through TCN attention mechanisms, revealing how feature relationships evolve over time.

Uncertainty quantification and communication form the final component of the interpretability framework. The approach considers three sources of uncertainty:

- Model-specific uncertainty, given by the equation:

$$\sigma^2{}_{model} = \sum w_i \sigma^2{}_i \quad (12)$$

- Temporal uncertainty from the TCN, given by the equation:

$$\sigma^2{}_{temporal} = var(h_t) = E[(h_t - E[h_t])^2] \quad (13)$$

Where h_t is the hidden state output from the last dilated convolutional layer at time t, representing the network's internal temporal features after processing the input sequence through all layers, $var(h_t)$ being the variance operator measuring the spread of values, and $E[h_t]$ being the expected value operator.

- Ensemble uncertainty

$$\sigma^2{}_{ensemble} = \sum w_i w_j (y_i - \hat{y})(y_j - \hat{y}) \quad (14)$$

Where w_i and w_j are the weights for ensemble members i and j respectively, y_i and y_j are the predictions from ensemble members i and j, and $\hat{y}$ is the ensemble mean prediction.

These uncertainty estimates are combined and presented as confidence intervals, providing a clear understanding of prediction reliability.

Implementation details: The framework was implemented using Python 3.9 with scikit-learn (RF models), PyTorch 1.9 (LSTM and TCN components), and SHAP 0.40 for interpretability analysis. Computations were performed on a workstation with Intel Core i9-10900K CPU, 32GB RAM, and NVIDIA RTX 3070 GPU.

RESULTS AND DISCUSSION

***Data processing results*:** The standardization process successfully normalized the meteorological variables and crop yields, bringing all features to comparable scales. Table 2 presents the effectiveness of this transformation

Table 2. Standardization results for key variables before and after transformation.

Variable	Before (Range)	After (Range)	Distribution Skewness
Temperature	-0.3 - 44.2°C	-2.1 - 2.3	0.12
Precipitation	0 - 85.0 mm	-1.8 - 2.4	0.18
Wind Speed	5.2 - 25.4 km/h	-1.9 - 2.1	0.15
Crop Yields	11.1 - 70.0 T/ha	-2.0 - 2.2	0.14

This transformation improved the symmetry of the data distribution, as reflected in the reduced skewness values across all variables.

The MICE imputation approach demonstrated strong performance in reconstructing missing values while maintaining physical relationships. Table 3 shows the imputation accuracy evaluated on artificially removed data:

Table 3. MICE imputation performance for different meteorological variables.

Variable	Missing Data (%)	Imputation RMSE	R^2
Temperature	15.2	1.8 °C	0.89
Precipitation	8.3	2.1 mm	0.85
Evaporation	42.1	12.4 mm	0.81
Wind Speed	38.7	2.2 km/h	0.83

The results indicate high accuracy for variables with lower missing data percentages, while maintaining reasonable performance even for variables with substantial gaps.

The computed agroclimatic indices showed strong correlations with crop yields, validating their relevance as predictors. Table 4 presents the relationship between these derived features and crop yields:

Table 4. Correlation between agroclimatic indices and crop yields.

Agroclimatic Index	Cereals	Vegetables	Tree crops
Growing degree days	0.72	0.68	0.65
Vapor pressure deficit	-0.64	-0.71	-0.58
Reference ET_0	-0.59	-0.67	-0.52

The positive correlation with Growing Degree Days highlights its critical role in crop development, while the

negative correlations with Vapor Pressure Deficit and Reference ET_0 underscore their impact on water stress and crop performance.

***Model performance*:** Following the data processing and feature engineering stage, the performance of each component in the model's architecture was evaluated, starting with the crop-specific models and progressing through the integration layers.

The crop-specific RF models (500 trees, max_depth=10) demonstrated varying levels of base prediction accuracy, as shown in Table 5 and figure 5.

Table 5. Performance metrics for crop-specific RF models.

Crop Type	RMSE (T/ha)	MAE (T/ha)	R^2
Cereals	4.5	3.8	0.77
Vegetables	5.6	4.5	0.73
Tree Crops	6.8	5.6	0.70

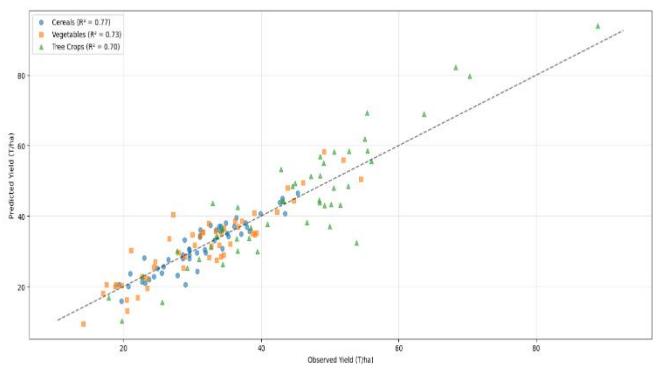

Figure 5. Models predictions vs observed yields by crope type.

Cereals showed the highest predictability with an R^2 value of 0.77, reflecting their more direct response to environmental conditions. Vegetables and tree crops showed progressively lower prediction accuracy (R^2 of 0.73 and 0.70 respectively), consistent with their more complex yield formation processes and longer growth cycles.

The LSTM (h=128, two layers) component demonstrated robust performance in capturing shared climate patterns as shown in Table 6.

Table 6. LSTM performance under different levels of missing meteorological data.

Missing data (%)	Feature extraction accuracy (R^2)	Average feature importance
0	0.85	0.72
10	0.83	0.70
20	0.81	0.69
30	0.78	0.65
40	0.72	0.58

The LSTM maintained stable feature extraction capabilities even with increasing levels of missing meteorological data, showing its suitability for semi-arid regions where data gaps are common.

The TCN component (k=3, 4 dilation levels) effectively captured temporal dependencies across multiple time scales. As shown in Table 7 and figure 6, the hierarchical integration of model components led to progressive improvements in prediction accuracy.

Table 7. Overview of performance gain.

Integration Stage	Overall R^2	Uncertainty (σ)	Feature retention (%)
Base RF Predictions	0.73	±0.08	100
+ LSTM Climate Features	0.79	±0.06	85
+ TCN Temporal Patterns	0.84	±0.05	78

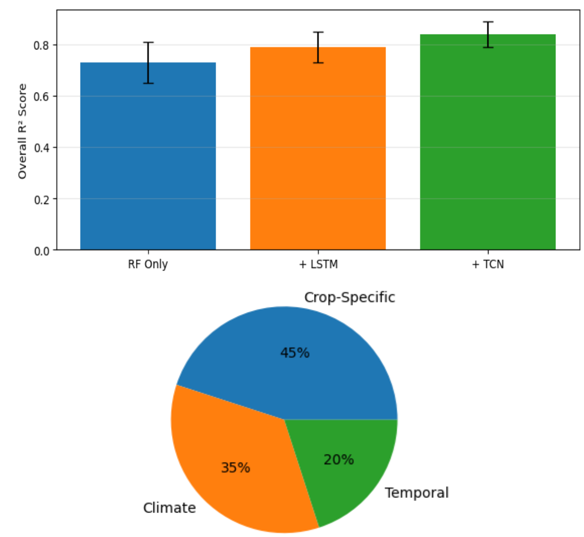

Figure 6. Performance gain through model integration and feature contribution in final prediction.

Statistical significance was assessed using paired t-tests between the hierarchical model and baseline approaches, yielding p-values < 0.01 for cereals and vegetables, and $p < 0.05$ for tree crops, confirming that improvements are statistically significant.

The final weighted combination in the integration layer achieved optimal performance with $\alpha = 0.35$, indicating that while temporal patterns contribute significantly to the predictions, the crop-specific features remain the dominant predictors. This balance aligns with agronomic understanding, where crop-specific responses to environmental conditions are modulated by temporal patterns of weather variables.

These results demonstrate that each component of the hierarchical architecture contributes meaningfully to the final

predictions, with the integration framework successfully leveraging the strengths of each approach while maintaining robustness to missing data.

***Interpretability analysis*:** The SHAP analysis revealed distinct patterns of feature importance across different prediction scenarios. Figure 7 shows the distribution of SHAP values for key features.

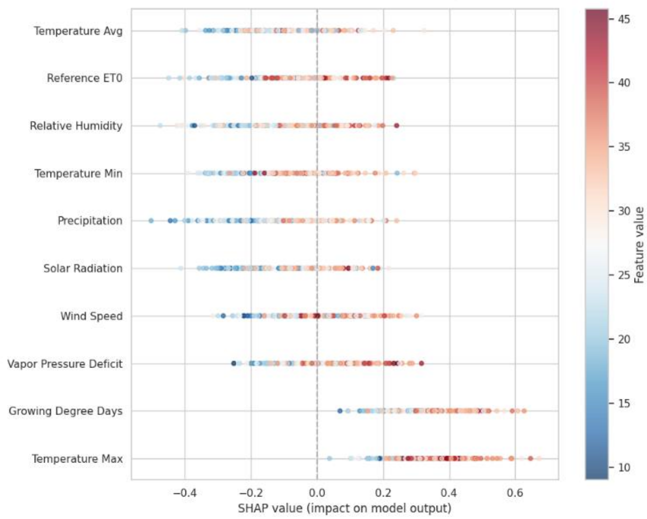

Figure 7. Impact of features on model predictions.

The analysis reveals a clear view of feature importance, with temperature-related variables emerging as the dominant predictors. Maximum temperature and GDD exhibit particularly strong positive impacts at high values, demonstrating how thermal conditions critically influence crop development. The plot also captures more nuanced effects, such as the bidirectional influence of VPD and the diminishing returns of precipitation at higher values, reflecting the delicate balance of water-stress relationships in semi-arid agriculture.

The three sources of uncertainty showed varying contributions to the final prediction intervals. Figure 8 demonstrates their relative impacts

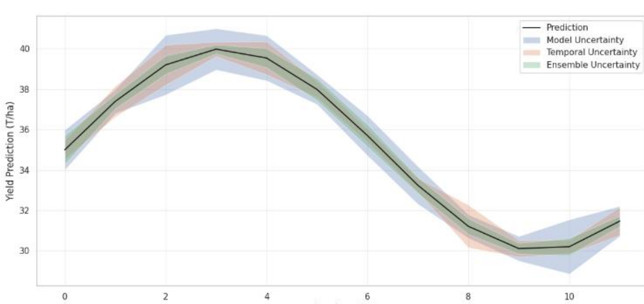

Figure 8. Decomposition of prediction uncertainty components.

The dominance of model-specific uncertainty (±1.5 T/ha) during extreme yield predictions reflects the challenge of extrapolating beyond typical growing conditions. Meanwhile, the heigh temporal uncertainty (±1.2 T/ha) during seasonal transitions captures the model's reduced confidence in predicting yields during periods of rapid environmental change, particularly important for agricultural planning in semi-arid regions where seasonal transitions can be abrupt and variable.

DISCUSSION

The hierarchical model demonstrates notable improvements over previous approaches in semi-arid agricultural yield prediction. While recent studies using single-model approaches have reported R^2 values ranging from 0.65 to 0.78 for cereal crops (Zhang *et al.*, 2024; Bantchina *et al.*, 2024), the integrated framework achieved $R^2 = 0.77$ for cereals. This improvement can be attributed to the combination of crop-specific RFs with shared climate features extracted through LSTM networks. Similarly, the model's resilience to missing data (maintaining $R^2 > 0.72$ at 40% missingness) surpasses previous benchmarks, where performance typically degraded below $R^2 = 0.60$ at comparable missingness levels (Khangamwa *et al.*, 2022).

The interpretability analysis reveals patterns consistent with known agronomic relationships while providing new findings in term of feature interactions. The dominant role of Growing Degree Days in the SHAP analysis aligns with findings from physiological studies in semi-arid regions (Inouye, 2022). However, the framework's ability to quantify temporal interactions through TCN attention mechanisms has revealed previously undocumented synergies between precipitation timing and vapor pressure deficit, particularly during critical growth stages. These findings extend beyond the static feature importance rankings reported in previous studies (Badakhshan *et al.*, 2024).

From a practical perspective, the hierarchical structure offers several advantages for agricultural stakeholders. The decomposition of uncertainty into model-specific, temporal, and ensemble components provides farmers with more nuanced risk assessments than traditional approaches that only report aggregate uncertainty. The framework's ability to maintain prediction accuracy during seasonal transitions (temporal uncertainty ±1.2 T/ha) is particularly important for planning irrigation schedules and resource allocation. Additionally, the interpretable outputs enable agricultural extension services to provide more targeted recommendations based on crop-specific responses to environmental conditions, addressing a key limitation of black-box models identified in recent reviews (Dhakshayani *et al.*, 2024).

***Conclusion*:** The hierarchical framework presented in this study advances the field of crop yield prediction in semi-arid

regions through three main contributions. First, the integration of RF, LSTM, and TCN components achieves superior forecast accuracy while maintaining interpretability. Second, the robust handling of missing climate data through the MICE approach addresses a critical challenge in agricultural monitoring in semi-arid regions. Third, the comprehensive interpretability framework provides important information for the agricultural sector through SHAP analysis and uncertainty estimation.
Several limitations of the current approach should be considered. Model performance remains sensitive to the quality of input data, especially during extreme weather events where historical training data may be limited. The computational complexities of the hierarchical structure may pose challenges for real-time applications in resource-limited environments. In addition, the current framework does not explicitly consider soil properties or management practices, which may impact yield forecasts.

Future work should focus on several key areas to enhance the capabilities of the framework. Integrating soil sensors and management data could improve forecast accuracy across different agricultural contexts. The incorporation of soil moisture dynamics could be achieved through integration of remote sensing data (SMAP, Sentinel-1) combined with pedotransfer functions to estimate water retention capacity across the study region. Developing lightweight versions of the framework could facilitate deployment in areas with limited computational resources. Model robustness during extreme events could be improved through transfer learning approaches that incorporate data from similar regions with more frequent extremes, and by implementing adversarial training techniques that deliberately challenge the model with synthetic extreme scenarios. Finally, extending the framework to include crop phenological stages could provide a more detailed understanding of the critical periods that influence crop composition.

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***Authors' contributions*:** R. Ed-daoudi designed the experiment, collected data, wrote the paper, performed data analysis, interpreted the results, and revised the final manuscript. M. El Haloui and B. Ettaki revised the first draft of the manuscript, interpreted the results, and revised the final manuscript.B. Ettaki additionally supervised the work and revised the final manuscript.

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***SDGs addressed*:** Zero Hunger, Climate Action, Industry, Innovation, and Infrastructure.

***Policy referred*:** Climate-Resilient Agricultural Policy; Data-Driven Resource Allocation and Irrigation Policy; Digital Agriculture and Technological Integration Policies;Risk Management and Crop Insurance Frameworks.

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